optimization

Meaning of optimization:-

↳ minimize or maximize of certain objective function.

Aim of optimization

↳ find best (optimum) solution for any optimization problem.

→ Examples of optimization Problems / Apps...

a) optimize Parameters of ANN model (weights & bias)

b) " Parameters of ANFIS model (Premise & antecedent Parameters)

c) Tuning Parameters of PID (get best value of K_P, K_I & K_D)

d) Getting best Placement of WI-FI access point for Indoor Positioning system (IPS)

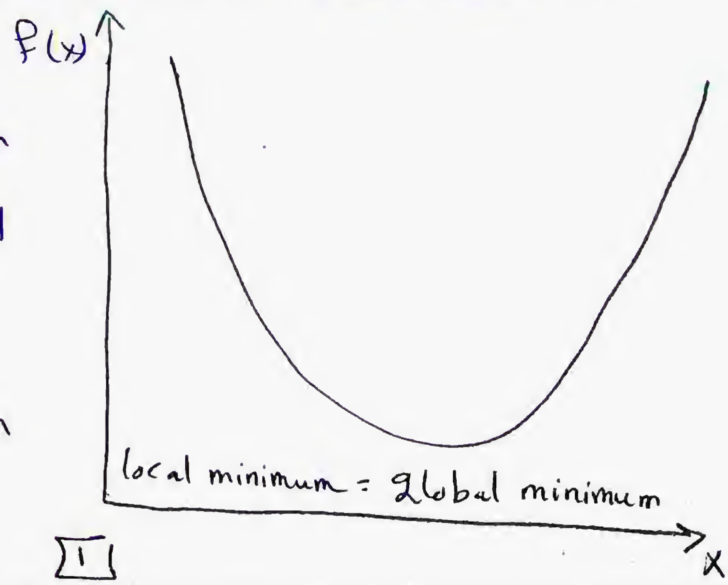
Notes

لـ كل (global optimum) هو (local optimum) لكن العكس مش دايماً صح.

* Unimodel Function

↳ has single local minimum which is itself the global optimum.

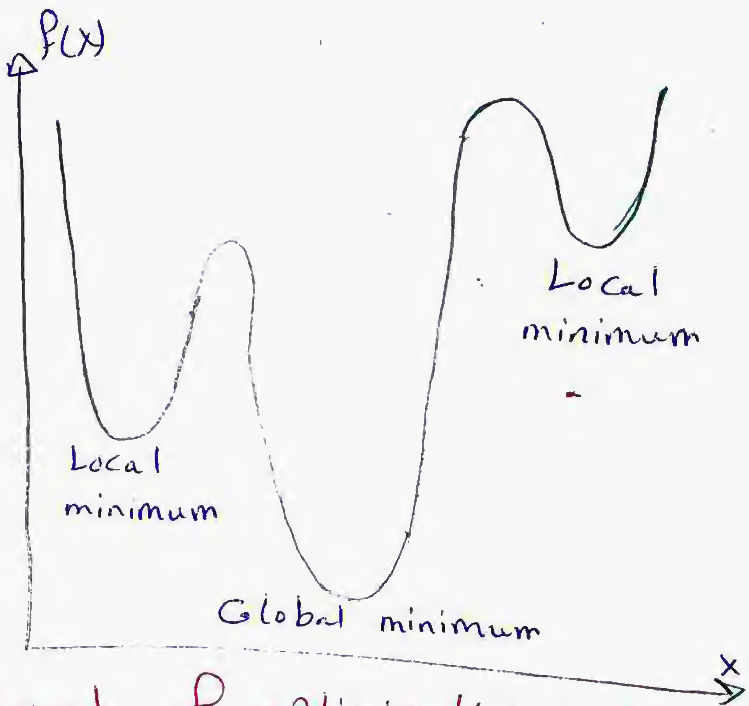
f(x) → objective function to be minimized.



* The ~~local~~ global minimum is the least among all local minimum.

2 Multimodel Function:-

→ has more than one local optimum and one global optimum ~~functions~~



* what is the ideal target of optimization problem?

↳ It is the global optimum (a good optimization algorithm does not get trapped in any local optimum)

Basic elements of optimization Problem

1) An objective function f

↳ function to be optimized (minimized or maximized)

2) The number of components or variables of the objective function that specifies the dimensionality of the optimization problem

$$f(x_1, x_2, \dots x_D)$$

where D is no. of variables specifies dimensionality of the problem.

$f(x)$, $X = [x_1, x_2, \dots, x_D]$ $1 \times D$ vector

3) sets of constraints forced on required solution

↳ most Problems Constrain at least search domains of the variables vector $X = [x_1, x_2, \dots, x_D]$

↳ aim of optimization is to find global optimum $X^* \subseteq R^D$ from allowable search domains, where $f(x^*)$ has the minimum value in search domain.

Classification of optimization Problems

Classification basis	Types of optimization Problem	
Dimensionality (D)	univariate (D = 1)	Multivariate (D > 1)
Linearity	Linear	Non Linear
Constraints	unConstrained (only search ranges of x_d are Constrained)	Constrainted (Additional Constraints are forced on x_d)
no. of optimum values	unimodel (one optimum only)	Multimodel
no. of objective	single-objective	Multi-objective (more than one objective to be optimized)

separability of variables X_d	separable function of $f(x_1, \dots, x_D)$ can be divided to D functions in form: $f(x_1) + f(x_2) \dots + f(x_D)$	Non-separable can't be divided.

Evolutionary optimization Algorithms
(Population-based " ")

↳ Evolutionary optimization algorithms are Population based of candidate solutions, not just one solution.

what is the basic characteristic of Population-based

↳ the iteration Policy depends on a Population.

what happens during the iteration?

↳ Population of constant size is maintained, and group of solutions is improved Progressively.

Note that "can be neglected"

↳ Having group of solutions "working together is the key of emulating behavior of biological organisms in modern biology-inspired optimization approaches (e.g. flock of birds, school of fish)

Examples of Evolutionary optimization Algorithm

1) Genetic algorithm (GA)
2) Bat algorithm (BA)
3) Artificial Bee colony (ABC)
4) Differential evolution (DE)
5) Ant colony optimization (ACO)
6) Particle swarm optimization (PSO)

Exploration & Exploitation

	Exploration	Exploitation
Meaning	↳ Find new solutions in search domains which havn't been evaluated before.	↳ try to improve the current found solution by performing small changes that lead to new solutions.
Variation of population members from one iteration to another	large	very small

Basic element affect on Exploration & Exploitation

1) Population size (no. of members in population) affects on exploration rate.

Large size of population $\Rightarrow \uparrow\uparrow$ rate of exploration.

2) Control Parameters of optimization algorithm

↳ affect on exploration and exploitation.

Notes

* optimization algorithm starts from larger exploration rate
  ↳ this allows the algorithm to cover large regions of search domains quickly.
* As iterations processes : exploration rate decreased
  ↳ allows to exploit the promising regions that are previously explored.

Benchmark Functions

↳ standard complex mathematical functions with different ch/s are used to test optimization algorithm "to evaluate efficiency & robustness"

How this test happens?

↳ بعد اختيار مجموعة الـ (benchmark functions) المناسبة ، الـ (Algorithm)
يبدأ يـ(run) مع الدوال دي لعدد N من المرات. كل
عملية (run) بتحتوي على (no. of iterations)

↳ نتيجة الاختبار بتطلع رقم الـ successful runs for each fn.

⇒ run is considered successful if algorithm reached the required global optimum.

Common Benchmark Functions

	Benchmark Functions	search range	Functions Properties
Sphere Function	$f_1(x) = \sum_{i=1}^{i=D} x_i^2$	$[-100,100]^D$	unimodel separable
Rosenbrock Function	$f_2(x) = \sum_{i=1}^{D-1} \left[100(x_i^2 - x_{i+1})^2 + (x_i - 1)^2\right]$	$[-2.048, 2.048]$	unimodel $(D<4)$ Multimodel $(D \geq 4)$ nonseparable
Ackley Function	$f_3(x) = 20 + e - 20\, e^{-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}} - e^{\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)}$	$[-30,30]^D$	Multimodel non separable
Griewank Function	$f_4(x) = 1 + \sum_{i=1}^{D} \frac{x_i^2}{4000} - \prod_{i=1}^{D} \cos\left(\frac{x_i}{\sqrt{i}}\right)$	$[-600,600]^D$	Multimodel non-separable
Rastrigin Function	$f_5(x) = \sum_{i=1}^{D} \left[10 + x_i^2 - 10\cos(2\pi x_i)\right]$	$[-5.12, 5.12]^D$	Multimodel separable
Schwefel Function	$f_6(x) = 418.9829\, D - \sum_{i=1}^{D} x_i \sin\left(\sqrt{\lvert x_i \rvert}\right)$	$[-500,500]^D$	Multimodel separable

Note that All of these functions are

*single-objective. *unconstrained